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Internet of things (IoT) platform competition: consumer switching versus provider multihoming

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Internet of things (IoT) platform competition: consumer switching versus provider multihoming

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Abstract

Platforms that are understood as a place or system coordinating the interaction of different stakeholders (e.g., service consumers and providers) may enable widespread adoption of IoT services and applications. However, the lack of interoperability between platforms may inhibit the diffusion of IoT services by preventing reaching a critical mass and reducing competition as it makes consumer switching and service provider multihoming prohibitively expensive. Moreover, network effects inherent in multisided platforms may lead to a monopoly power in IoT market.

This paper analyzes the effect of consumer switching costs and provider multihoming on market structure and competition by means of agent-based modelling. Simulation results suggest that service provider multihoming plays a key role in increasing market competition when switching costs decrease due to, for example, consumer data portability.

Keywords: IoT, interoperability, network effect, data sharing, consumer switching, service provider multihoming, coopetition

Introduction

The widespread adoption of IoT services and technologies requires an ecosystem typically built around a platform to facilitate the interaction of the involved players. Since IoT covers an extremely wide area of applications, multiple platforms emerge; however, they are often sector specific and lack interoperability, forming isolated silos. From this perspective, a main regulatory concern is the lack of cooperation between the existing platforms.

In the field of platform economics, Rochet and Tirole (2003) suggest that in markets with network externalities and two or more interacting sides, a dominant platform will emerge and the market will exhibit high market concentration and monopoly power. In such a scenario, platforms compete aggressively to rapidly get those users who are most sensitive to price, which in turn can attract the users on the other side of the platform.

Boudreau and Hagiu (2009) highlight the importance of platform rules, beyond pricing, to achieve a socially desirable outcome. Such rules include legal, technological and informational aspects. For assuring competition, many authors have emphasized the importance of interoperability between platforms (Manyika et al., 2015; O'Halloran & Kvochko, 2015). For instance, Schiff (2003) argues that a compatible duopoly achieves higher social benefits than a noncompatible one. Moreover, Rochet and Tirole (2003) argue that the existence of multihoming¹ on one side of the platform

¹ Multihoming refers to the ability of the user or provider of maintaining several concurrent service subscriptions or provisions.

incentivizes the competition on the other side. However, platform owners may utilize exclusive contracts to prevent service provider multihoming (Armstrong & Wright, 2007).

In a future IoT scenario, platform interoperability is needed to achieve a critical mass of users. Platform interoperability may enable data sharing, which allows users to switch from one platform provider to another without losing their data. Furthermore, recently introduced European Union General Data Protection Regulation (EU GDPR) established a requirement for consumer data portability, which promotes the development of tools or mechanisms to ease data transfer from one platform to another (De Hert et al., 2017) decreasing consumer switching costs. In consumer IoT, such data transfer may take place either between service providers or between IoT platforms, depending on the entity managing consumer data. In any case, seamless implementation of data portability requires higher interoperability between exchanging parties (De Hert et al., 2017). In addition to enabling user switching, platform interoperability can facilitate service provider multihoming as it can decrease the cost of application development for multiple platforms.

In networked markets, regulatory authorities incentivize competition through decreasing consumer switching costs, which are traditionally seen as a barrier to enter a market (Klempeter, 1987). For example, in the mobile telecommunications industry the implementation of mobile number portability (which diminishes switching costs) resulted in lower retail prices in many countries (Sánchez & Asimakopoulos, 2012). However, this may not be always the case. For instance, Chen (2016) and Lam (2017) found that decreasing switching costs may negatively affect competition in industries with high network effects. Chen (2016) suggests that lowering consumer switching costs may increase market concentration under high network effect and without a viable outside option (i.e., an alternative service or platform), but at the same time may decrease market concentration if such option exists. On the other hand, Lam (2017) argues that the decreasing switching costs on one side of the platform (e.g., consumers) may increase the price on the other side of the platform (e.g., service providers) and thus may not have the expected positive effect on social welfare.

The relation between competition and cooperation (i.e. coopetition²) has been understudied in the IoT literature. While many authors agree that interoperability (i.e. cooperation) is required for reaching a critical mass of users, it may also lead to a decrease in switching cost which incentivises competition. On the other hand, interoperability facilitates provider multihoming. The overall effect of user switching and provider multihoming has not been properly studied. However, there have been some recent attempts in the mobile telecommunications industry to study the dynamics of coopetition. For example, Karhu, Tang & Hämmäläinen (2014) compared the level of competition and collaboration in mobile operating systems (Apple, Microsoft and Android), arguing that both strategies are widely utilized in the mobile ecosystem. In this study, cooperation is measured by the number of services a platform offers through third parties, while competition is measured by the number of services a platform produces by itself. Also, Basaure, Suomi & Hämmäläinen (2016) compared the main competitive mechanisms (end-user multihoming) against cooperative mechanisms (roaming and dynamic spectrum access) in the mobile telecommunications, concluding that both cooperative and competitive mechanisms increase economic efficiency in a similar manner.

² Coopetition is a relationship between actors (i.e. firms) which are simultaneously competing and cooperating

This study aims to further contribute to analysing the dynamics of coopetition by means of agent-based modelling. The starting point of this study is that both competition (incentivized through consumer switching) and cooperation (achieved through interoperability, which enables data sharing and service provider multihoming) are needed to optimize social welfare created by emerging IoT applications. Thus, this paper addresses the following research question: how do consumer switching costs and provider multihoming affect market structure and competition of emerging IoT platforms? In practice, this work aims to evaluate the effect of different policy decisions on the competition of IoT platforms.

Background

IoT platform

With the increasing attention paid to the IoT, a growing number of products and services are marketed as IoT platforms. Such platforms are often a core component of an IoT solution; they provide interconnection between heterogeneous sensors and actuators, help to manage them, and finally store and analyze the data they produce (Mineraud, Mazhelis, Su, & Tarkoma, 2016). Apart from the IoT platform, a typical IoT solution includes four other layers - sensors and actuators, device, gateway, and application (Guth, Breitenbucher, Falkenthal, Leymann, & Reinfurt, 2016). Although on an abstract level IoT solutions are often similar, due to the lack of widely accepted standards, their implementations often differ in architecture thereby hindering interoperability. To combat this problem, several standardized reference architectures for IoT were introduced (Weyrich and Ebert, 2016), which specify structure and functions of IoT platforms. In this work, the modeled platforms form a multi-sided market enabling service providers to build applications based on the data collected by IoT devices, although current IoT platforms often lack an open marketplace for third-party developers (Mineraud et al., 2016). The data is assumed to belong to consumers, who therefore have the power to grant service providers access to it. The core functions of an IoT platform is to enable the data collection, storage and utilization. Such platform can be exemplified by GSMA IoT Big Data Framework Architecture (GSM Association, 2016). Unlike many others mostly industrial internet-focused reference architectures for IoT, such as the ones proposed by ISO (draft) (ISO/IEC, 2016) and Industrial Internet Consortium (Lin et al., 2017), GSMA IoT architecture explicitly focuses on data and supports an ecosystem of third party developers. To abstract technical complexities unnecessary for this research, this paper takes a high-level view of a platform, as illustrated by Figure 1. Therefore, the platform also fits to some extent other IoT reference architectures, such as ISO and Industrial Internet Consortium, which provide more detailed views.

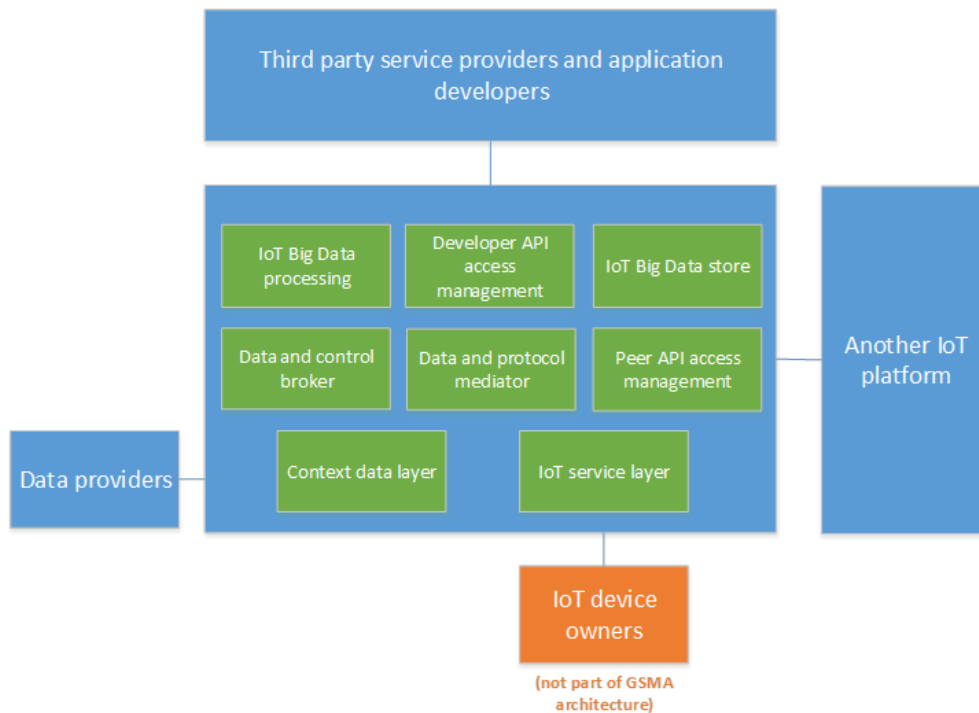


Figure 1: Abstracted view of GSMA IoT big data framework architecture (GSM Association, 2016)

Further sections present the state of the art development of mobile Health IoT platforms as a way to illustrate the dynamics of consumer IoT applications.

Mobile Health

Wearable and digital health devices can be viewed as an early and advanced consumer IoT vertical. Already in 2016, the number of connected wearable devices globally reached 325 million, and it is expected to increase to 929 million by 2021 (Cisco, 2017). Wearable and digital health devices enable tracking of multiple physiological parameters, including heart rate, electrocardiogram, activity, and blood pressure, thereby forming a part of mobile health (mHealth) – a field that uses mobile devices to support achieving health targets (Olla and Shimskey, 2015).

Large mobile health device producers typically have a proprietary web API (Application Programming Interface) platform that enables third-party complementors (software developers and other service providers) to access the data of consumers upon receiving their consent. Such data sharing can potentially increase device sales, which therefore motivates producers to invest in platform development. Since various health and wellness-related data are complementary, data sharing enables combining the data and enhancing the value it creates.

Figure 2 illustrates the architecture of data platforms in mobile health. As mentioned above, device producers, such as Garmin, Polar, and Fitbit, have vendor-specific platforms, which allow querying a web platform database and copying user data to service provider cloud or mobile application. Furthermore, there are data aggregator platforms, such as Google Fit, Apple Health, and Samsung Health that offer to consumers a single point of storing their mHealth data, and to device producers and other service providers – a hub for sharing the data together with the tools to assist in application development (e.g., Farshchian and Vilarinho, 2017). However, mHealth companies often share with

the aggregators only basic summary data due to various reasons, including the unsuitability of data models and unwillingness to lose control over the data sharing. Some platform providers, such as Fitbit, Google Fit, and Samsung Health, allow third parties utilizing their cloud platforms as the primary data storage location. While most of the mHealth platforms are web-based, Apple Health is one of the few exceptions that provide a local platform to store and share the data on the iPhone (Farshchian and Vilarinho, 2017).

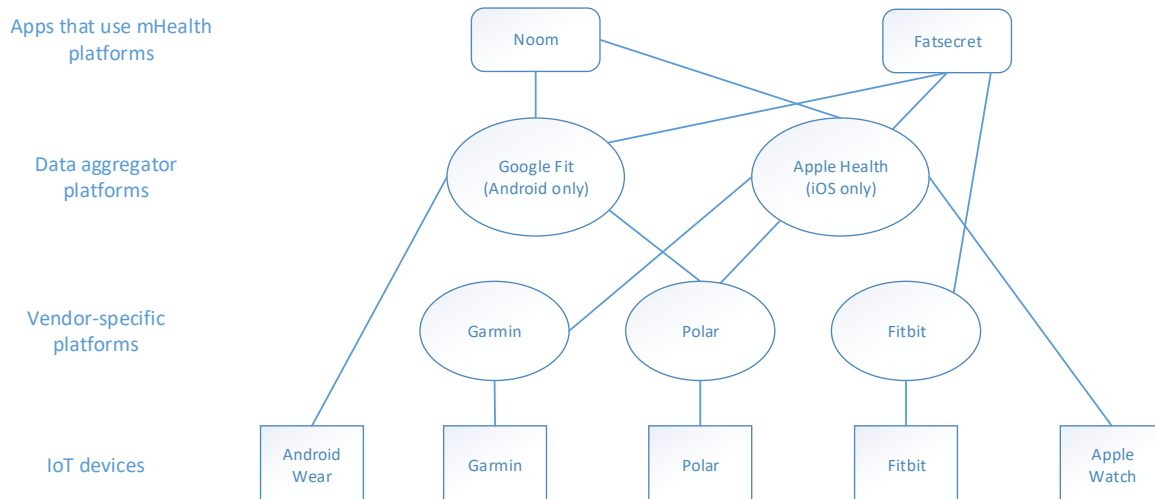


Figure 2: Data sharing platforms in mobile health

Despite the high interconnectedness of service and platform providers in the mHealth domain (Grundy et al., 2017), a consumer willing to change a platform still incurs considerable switching costs associated with the device and data. Thus, currently, many platforms are vertically integrated with the device and service, which prevents using the same device with another platform. Even if a device producer shares the data with a data aggregator, which gives the consumer some freedom in choosing a platform and service provider, such data sharing and its related decrease in switching costs are limited. Another switching cost is associated with the historical data, which is typically lost after switching from one platform to another and it represents a cost for the consumer. Moreover, some applications require the data for feeding the algorithms and providing better service. Currently, although some platform and device providers, such as Garmin, provide tools for migrating the data from some other platforms, such as Fitbit, these tools are limited to some types of data (DC Rainmaker, 2016).

Service providers that use mHealth platforms are also subjects to a platform switching cost. Thus, when the license agreement with a data platform provider is terminated, the terms typically require complementors to remove all data that was received from the platform (e.g., Nokia, 2017), which in some cases constitutes a switching cost since maintaining the data may be important for improving the algorithms and services. Furthermore, service providers that used a platform for storing own data have a switching cost associated with moving the data to another platform. Such a switching cost may be high due to the lack of standardized data formats and web API implementations (de Arriba-Pérez et al., 2016).

To increase the reach of potential customers, large mHealth companies often multihome on several data sharing platforms as, e.g., the providers of applications Noom and Fatsecret, as well as wearable device manufacturer Polar (Figure 2). In this case, Polar acts as a service provider connected to Google's and Apple's platforms, although it has own platform.

Potential evolution

Although currently mHealth platforms are mostly used for sharing the data inside consumer health and fitness domain, in future the stakeholders of the traditional healthcare industry, such as doctors and payers, may start using the platform (Comstock, 2014).

Presently, consumer and service provider switching costs are high. In future, device-related switching cost can be decreased if higher interoperability between devices, service providers and platforms is achieved. This is possible, for example, if Bluetooth Generic Attributes (GATT) specifications, which are intended to ensure interoperable data structures (Bluetooth, n.d.) are widely adopted. Currently, GATT profiles are implemented in, e.g. some heart rate sensors, which enables their use with any compatible Bluetooth device. Moreover, the EU GDPR should decrease data-related switching cost. Finally, the development of standards and specifications for data exchange, such as FHIR³, can ease the data transfer between platforms and enable service provider multihoming through the standardization of data formats and APIs.

For the purpose of this analysis, mHealth data sharing platforms, such as Google Fit or Samsung Health, are viewed as IoT platforms. Consumers select the platform, which collects their data to the cloud database, and upon obtaining the consent, provides access to this data to third party service providers, such as application developers, doctors, and insurance companies, which use the data in own service provisioning. Both consumers and service providers are subjects to the terms and conditions that they have to accept for using the platform, which may include, e.g. the requirement for service providers to remove the data upon the termination of the license agreement with a platform owner.

Methodology

This work utilizes agent-based modelling and simulation for describing the interaction between different stakeholders in a platform. Agent-based modelling performs a bottom-up study of complex adaptive systems, which emphasizes the adaptation of individuals given a simple set of rules. This study defines consumers, platforms and service providers as main interacting roles (i.e. agents) formalized in a horizontally differentiated simulation area⁴. They interact given different switching costs and multihoming conditions.

Agent-based modelling is especially suitable when decision making is distributed at micro (agent) level, even though some rules are still applied in a centralized fashion. Therefore, this simulation

³ <http://hl7.org/fhir/>

⁴ Horizontal differentiation refers to those differences between products and services which are not affecting price and quality

technique is appropriate for analysing the impact of different interoperability and multihoming scenarios on platform competition considering the interaction of micro-level agents.

The main advantage of agent-based modelling is high flexibility for describing the interaction of heterogeneous agents, bringing together micro-individual behaviours, interaction patterns and global regularities. Agent-based modelling carries some disadvantages, such as scalability constraint with large-scale systems with thousands of agents and the difficulty of validating the models against empirical data. However, for this study these drawbacks are not critical since we focus on competition dynamics rather than on detailed system performance.

Agent-based modelling has been recently utilized to analyse the ICT ecosystem. For example, Basaure, Suomi & Hämmäinen (2016) and Finley & Basaure (2018) modelled the interaction between networks and mobile users. The interaction between different agents in a two-sided platform has been modelled by Meyer (2012), who paid particular attention to path dependence in the mobile ecosystem.

Model

This section proposes a model for analyzing the interaction between the involved stakeholders in a cloud-based IoT platform: consumers, platform providers and service providers. The model distinguishes two types of service providers - main service providers and complementary service providers - to describe a multi-sided platform, since emerging IoT platforms are often intended for multiple types of users (Porter & Heppelmann, 2015). Thus, a consumer values a main service provider more if a complementary service provider is also available (e.g., a health service provider or a car maintenance service is more valuable for the consumer if an insurance service is also available).

The proposed model analyses consumers and service providers by locating them in a simulation area that is horizontally differentiated. The horizontal differentiation is based on the Hotelling model of spatial competition (Hotelling, 1929), which basic form describes firms competing in a one-dimensional characteristic space and has been expanded into a two-dimensional by several authors (Eaton & Lipsey, 1975; Economides, 1986 and Veendorp & Majeed, 1995) to represent a more realistic situation in which firms compete by more than one characteristic. Thus, agents are located in a two-dimensional characteristic space and they move in this area according to changes in supply (i.e. service providers) and demand (user preferences and needs). The simulation setup is described in Figure 3 :, where triangles depict a platform, persons depict consumers, faces depict main service providers and stars depict complementary service providers. Each dimension represents an important characteristic of the product and the resulting differentiation cost is defined by the Euclidean distance; in other words, both characteristics are equally important and the cost of differentiation is linear.

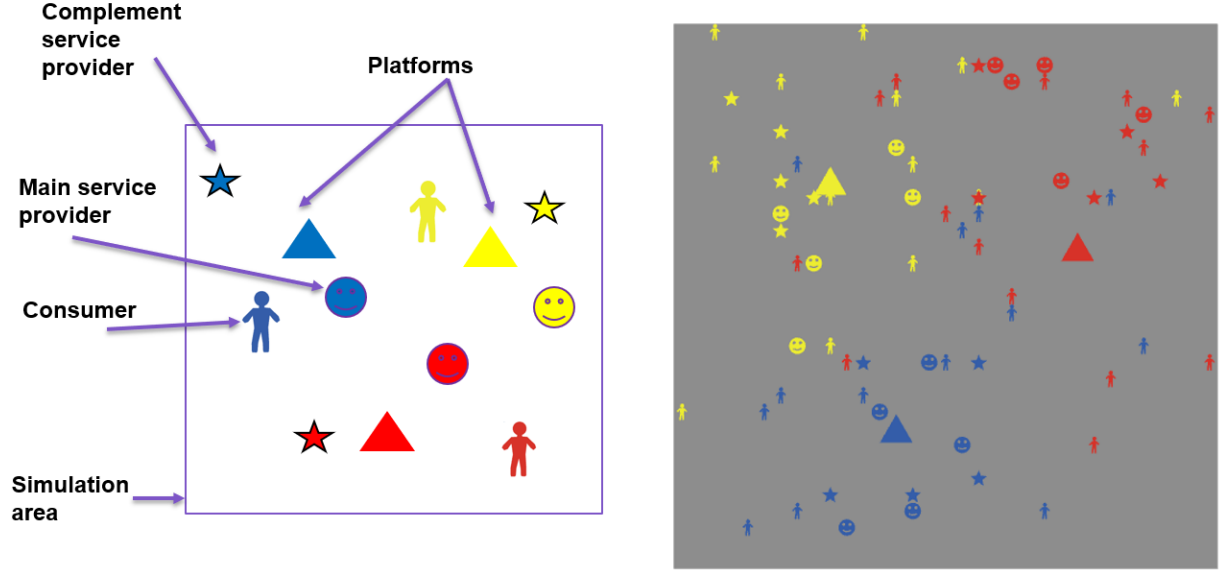


Figure 3 : (left) simulation setup for a horizontally differentiated area. (right) model implementation by Repast Symphony 2.4

For the user, the value of joining a platform depends on the type of network effect, which may change from case to case. In general terms, each user will make the decision on switching to another platform considering the net benefits obtained from the new platform minus the switching costs of changing from one platform to another. Thus, the value of joining a platform can be expressed as follows:

$$(1) V = U_{sa} + U_{ne} - sc - p,$$

where V is the value of joining a platform, U_{sa} is the standalone utility or net valuation of the platform without externalities and switching costs, U_{ne} is the utility due to network effect, sc are the switching costs and p is the price of service subscription (per service, per platform or both). The standalone utility U_{sa} can be defined as the utility the user assigns to the platform quality (U_q) minus the costs due to horizontal differentiation c_d (distance between the user and the platform):

$$(2) U_{sa} = U_q - c_d$$

The network effect can be modelled by negative exponential functions, as depicted by Evans and Schmalensee (2010). These functions describe the existence of a critical mass, after which the user is more likely to join the platform. This model utilizes the following functions:

$$(3) U_{ne_low\ critical\ mass} = 1 - e^{-k_0 * \frac{N_u}{N_{max}}}$$

$$(4) U_{ne_high\ critical\ mass} = 1 - e^{-k_1 * \frac{N_u^2}{k_2 + N_u}}$$

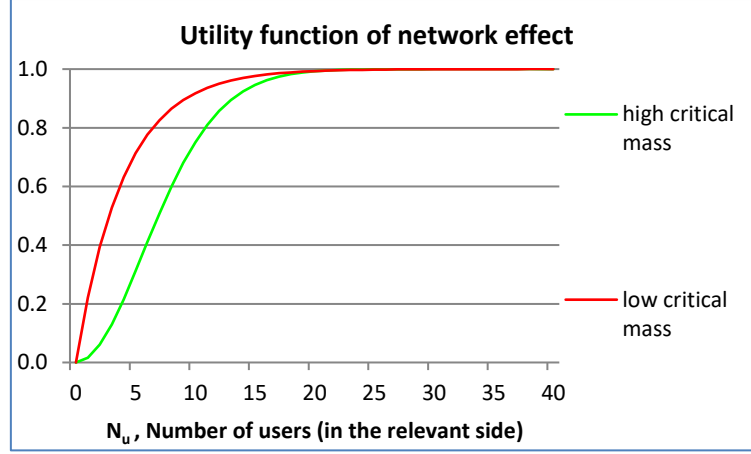


Figure 4: utility function for 40 users (N_{max}), where $k_0 = 10$, $k_1 = 1$, $k_2=62$

Equation 3 represents a general negative exponential function, where N_{max} is the total number of users in the relevant side(s) of the platform, N_u is the actual number of users and k_0 is a parameter giving the shape to the curve. Equation 4 represents an S-shaped curve, in which N_u is the actual number of users in the relevant side(s), while k_1 and k_2 give the shape to the curve. Graphical representation of these equation with example parameters are shown in Figure 4. For the simulation, high critical mass means that a 75% of the total value is achieved by 25% of users, while low critical mass means that a 90% of the total value is achieved with the same amount of users. This model describes a multi-sided platform in which each side values all other sides of the platform. Thus, a consumer values a main service provider if a complementary service provider is also available. In the same way, service providers value both consumers and complementary service providers, and complementary service providers value consumers and main service providers. In practice, the total value of network effect is taken as the minimum between the value of the network due to different types of users at other sides of the platform as expressed by equation 5. Thus, the value of the network effect is calculated separately for each agent type and then defined by the side with least users, indicating that the weakest side behaves as a bottleneck.

$$(5) U_{total\ ne} = \min(U_{ne\ of\ side\ 1}, U_{ne\ of\ side\ 2})$$

Switching costs are modelled by describing the lock-in effect due to technology and data. On the consumer side, the user gets locked-in when buying a new device (e.g., wearable). When the value of the device depreciates over time, the lock-in effect diminishes. At the same time, the consumer gets locked-into the data obtained by the service. The data generated by the consumer improves the quality of service and after some time causes a considerable switching cost, if upon switching to another platform this data is totally or partially lost. Consumer switching costs are depicted in Figure 5.

On the other side, the service provider also gets locked into a platform. The initial investment for developing the service (e.g., application development) represent an irreversible cost (i.e. sunk cost), which acts as a switching cost for the service provider. For changing from one platform to another, the service provider should duplicate the initial investment if platforms are not compatible. In addition, a service provider gets locked into the data as well. A service provider utilizes the aggregated data from consumers to offer an improved service. By switching from one platform to another, the

service provider is not able to easily reutilize this information if data sharing is not possible due to the differences in data formats or other reasons. Service provider switching costs are depicted in Figure 6.

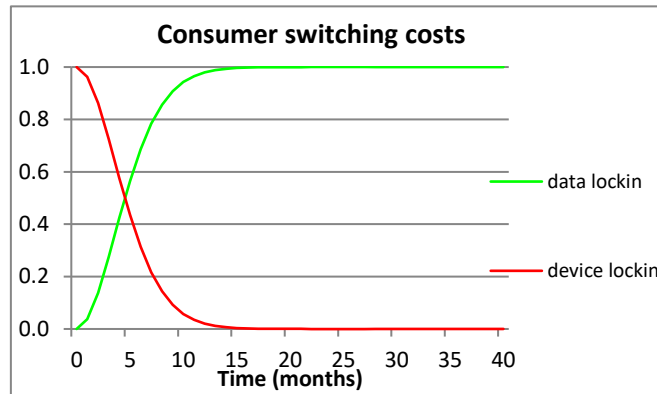


Figure 5: Graphical representation of consumer switching costs

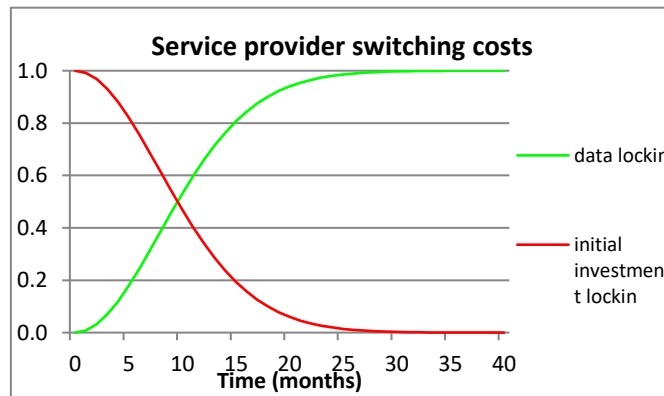


Figure 6: Graphical representation of service provider switching costs

The model in this paper assumes that service providers multihome; i.e. they may enter to more than one platform simultaneously to increase customer reach. Typically, large service providers have higher probability of multihoming (Hyrnsalmi et al., 2012). To describe such a situation, this model assumes that service provider budgets are uniformly distributed ($\sim U(a, 2a)$), where a is the investment required for entering a platform (i.e. costs of developing an application). If platforms are not interoperable, most service providers will enter one platform only, since the expenses of entering two platforms would be $2a$. If interoperability increases, the costs of developing an application can be shared between platforms. For instance, if 50% of the investment can be reutilized, the costs of entering two platforms will decrease to $1.5a$ and half of the service providers will multihome.

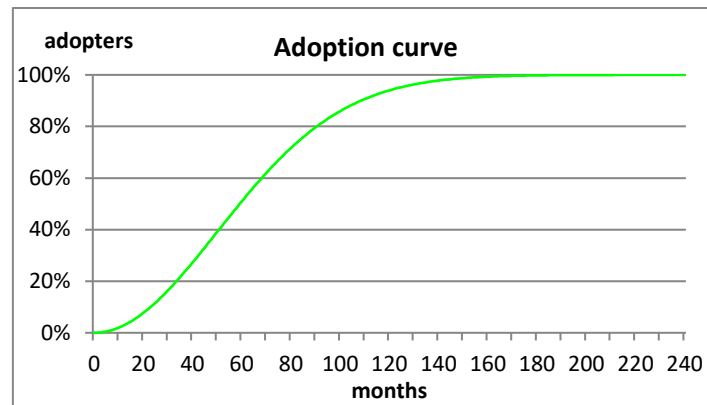


Figure 7: Adoption curve, where y axis indicates the number of adopters in percentage

Scenarios

This analysis defines five scenarios describing possible switching cost situations, as specified below and summarised in Table 1:

1. Base or first scenario: High switching costs and no interoperability. The industry is vertically integrated and consumer devices are integrated to one platform. Data sharing is not possible or very expensive. For example, this means that a wearable device is locked into a specific platform. In this scenario, data format is not standardized.
2. Second scenario: consumer device is unbundled from the platform. Consumer devices may easily switch from one platform to another, but data cannot be easily transferred. For example, Bluetooth GATT-compatible sensors are nowadays unbundled from platforms.
3. Third scenario: consumer data portability (e.g. in line with EU GDPR). Regulatory requirements push service or platform providers to supply the tools for migrating consumer data. In this scenario the device is bundled with the platform, meaning that platform switching requires acquiring a new device (wearable)
4. Fourth scenario: device unbundling and consumer data portability. This scenario combines the second and the third scenarios. In this scenario, consumer switching costs are in their minimum level, since devices are unbundled from the platforms and consumer data can be easily transferred.
5. Fifth scenario: full data sharing including consumer and service provider data. As an extension of the consumer data portability, service providers storing data at a platform cloud may easily transfer their data to another platform cloud. For instance, a health service provider or insurance company can easily transfer their data or reutilize their stored data across different platforms.

Table 1: Summary of analysed scenarios

	Presence of switching costs			
	Consumer device	Consumer data	SP investment	SP data
Scenario 1 (Base)	✓	✓	✓	✓
Scenario 2		✓	✓	✓
Scenario 3	✓		✓	✓
Scenario 4			✓	✓
Scenario 5	✓		✓	

Each switching cost scenario is run for different cases and compared to the base case (Table 1):

1. Network effect: The first case tests the impact of the network effect by utilizing the equations 3 and 4 and by performing an additional sensitivity analysis of network effect strength by varying parameters k_1 and k_2 of equation 4.
2. Multihoming: The second case explores the impact of service provider multihoming on market concentration by analysing the impact of high reutilization rate (70%) to all scenarios, and additionally by looking at different reutilization rates for selected scenarios. Finally, the impact of multihoming is tested for a high initial market concentration.
3. Differentiation: In the third case, the simulation is run with different distance costs; in other words, with different differentiation levels. In the base case (i.e. lower differentiation), the maximum distance cost is as high as the maximum value caused by network effect. In the higher differentiation case, cost of distance is doubled as compared with the base case. The distance cost is further varied until it reaches three times as much as the base case.
4. Adoption: In the last case, consumers and service providers are gradually adopting the platform service following an s-shaped curve as depicted in Figure 7, where the market achieves a 50% of saturation during the first 5 years and 90% during the first 10 years. For this case, service providers enter the market a little earlier than consumers.

The simulation scenarios and cases are summarized in the following Table 2.

Table 2: Summary of simulated cases and scenarios

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
	High switching costs	Device unbundling	Consumer data portability	Scenarios 2 and 3 combines	Full data portability
Base case	High critical mass, no multihoming, low differentiation, saturated (not growing) market and low initial market concentration (HHI equals approx. 0.35)				
Network effect	High versus low critical mass (as defined in Eq. 3 and 4 and Fig. 4)				
				An additional sensitivity analysis on critical mass for scenarios 4 and 5	
Multihoming	No multihoming versus multihoming (70% reutilization rate). Additionally, both multihoming and no multihoming are tested with a high initial market concentration				
				Additional sensitivity analysis for reutilization rate for scenarios 4 and 5	
Differentiation	Low versus high differentiation (where unit cost of distance is two times in the higher than in the lower differentiation case)				
				Additional sensitivity analysis for differentiation for scenarios 4 and 5	
Adoption	Growing (Fig. 7) versus saturated market				

Simulation setup

This work simulates the evolution of the market over 20 years, each iteration describing a time period of one month. For each scenario, each simulation run is repeated 100 times to obtain average values and related standard errors. The model considers 40 consumers, 20 main service providers, and 20 complementary service providers. Thus, each consumer in the simulation represents several thousand consumers in the real world. The adoption case begins with 20 consumers, 10 main service providers and 10 complementary service providers, and the number of agents is increased following the s-shaped curve of Figure 7 until reaching a saturation point of 80 consumers, 40 main service providers and 40 complementary service providers.

In some cases, a service provider may exit the market if it is serving too little consumers in its location. In this case, the simulation allows new service providers to enter the market until it reaches its saturation point. When entering the market, a new service provider chooses the location with the highest consumer-service provider ratio. Consumers move faster than service providers (10 times faster), since consumer needs and tastes are dynamic, and the reaction of service providers lags.

Figure 8 describes one simulation iteration. At the beginning of a simulation run, all agents are initialized. At each iteration (which equals one month) consumers and service providers may enter the market, if the saturation point has not been reached (consumers enter gradually only in the adoption case, service providers enter gradually constantly since they may exit the market). After that, they move following a random walk. Then, consumers and service providers evaluate whether to stay in the same platform or to change to another. They consider the utility obtained from each platform including the costs of switching.

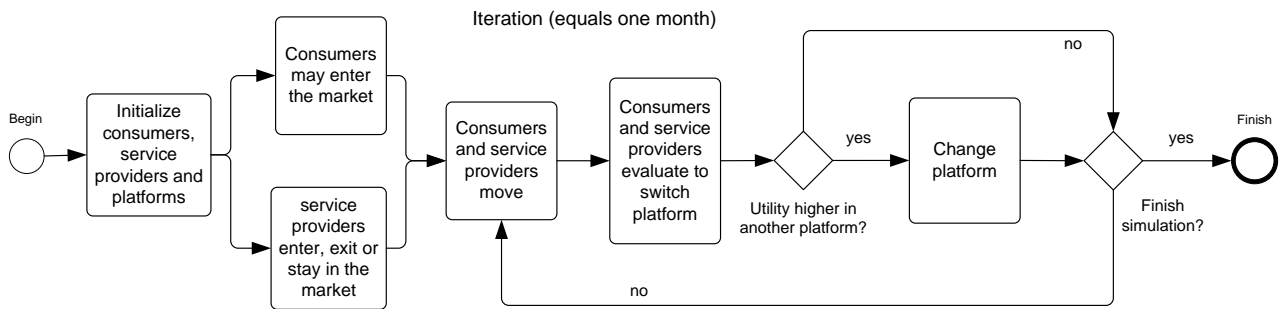


Figure 8: Simulation diagram describing one simulation iteration

At each iteration, the total number of users is computed for each platform. At the end of one simulation (20 years), the average number of users (i.e. consumers and service providers) is calculated for each platform and concentration index (Herfindahl-Hirschman Index, HHI) is assessed for the whole period. Each simulation run is repeated 100 times for each scenario for achieving low error margins. Each repetition has the same initial parameters (including seed number), except the location of consumers and service providers, which is randomly assigned following a uniform distribution.

In Figure 9 depicts the number of users in each platform during one run (left) and the resulting HHIs for hundred runs with equal parameters (right). Since the number of users of each platform may typically vary in time around an average, the HHI is calculated by averaging the number of users at

each platform during the whole simulation period. However, in each simulation run, the first 2 years are not considered in the results to remove the transient state. This way of computing the HHI describes better the dynamics of competition. Figure 9 (right) shows that HHI may significantly change from one run to another, evidencing that results are dependent on the initial conditions. To express that volatility in the results, this analysis calculates the mean and standard deviation of the obtained results.

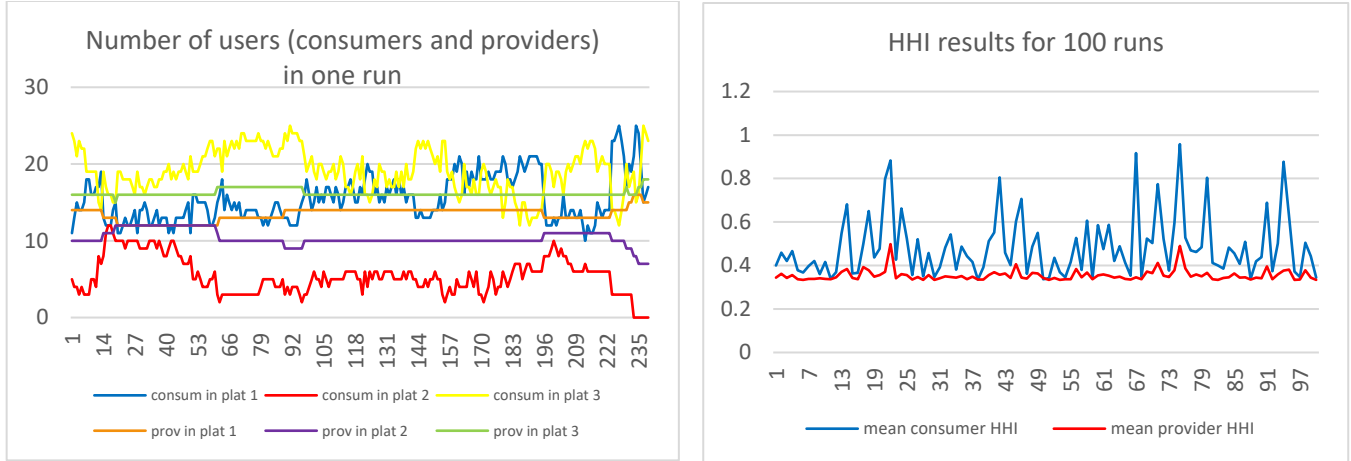


Figure 9: Simulation calibration: one run (left) and 100 results for HHI (right)

Results

The simulation results are presented as follows. Figure 10 depicts how the HHI varies for the five scenarios with different critical mass levels. The figure shows average values with standard error margins (left) and standard deviation values (right). These results suggest that decreasing switching costs results in higher market concentration. In the first scenario (high switching costs), the concentration index remains near the starting point (approx. 0.35 HHI with low standard deviation) indicating that market shares are stable. As switching costs are decreased, the concentration index increases especially on the consumer side. Note that the consumer concentration index shows a higher variation (both in average and standard deviation values) because the consumer is far more agile than a service provider, in line with the assumptions of the model. A higher standard deviation reflects a market with higher fluctuations in market concentration over 100 simulated runs (scenarios 2, 3 and 4). In scenario 5 (full data portability), the winner platform rapidly obtains the whole market. This dynamic suggests that after diminishing switching costs at all sides of the platforms, consumers and service providers will favour the platform with higher number of users, which will result in higher market concentration if network effect is strong. This observation is highly relevant, considering the effort from regulatory authorities for diminishing switching costs related to data portability.

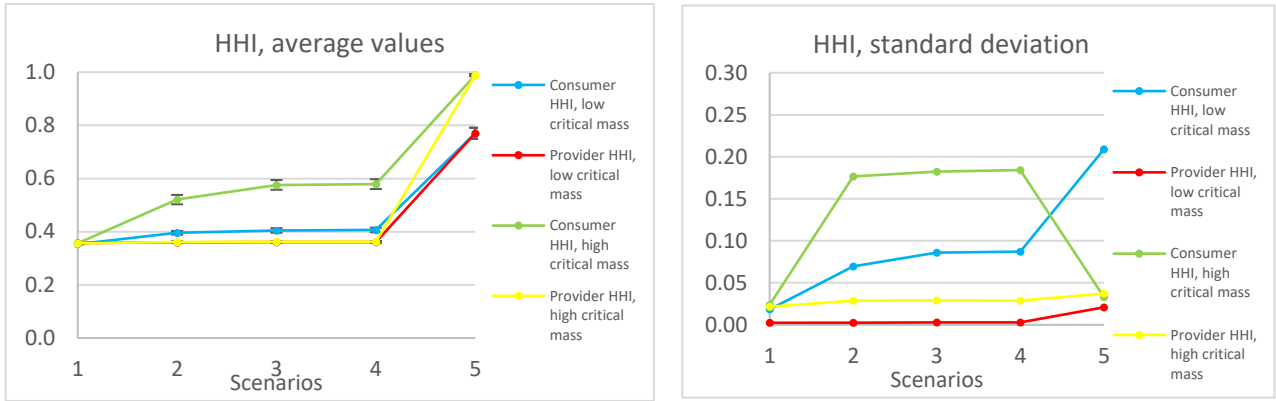


Figure 10: Simulation results for high versus low critical mass: (left) average and (right) standard deviation values

Additionally, a sensitivity analysis on network effect is depicted in Figure 11, where scenarios fourth and fifth are tested with different strengths of network effect. With this purpose, the model utilizes critical mass variations of equation 4, measured as the number of users required to achieve a 75% of the maximum utility value. Figure 11 (left) illustrates such critical mass variations with a total number of 40 users. The results are depicted in the right graph of the same Figure, in which market concentration increases almost linearly with critical mass.

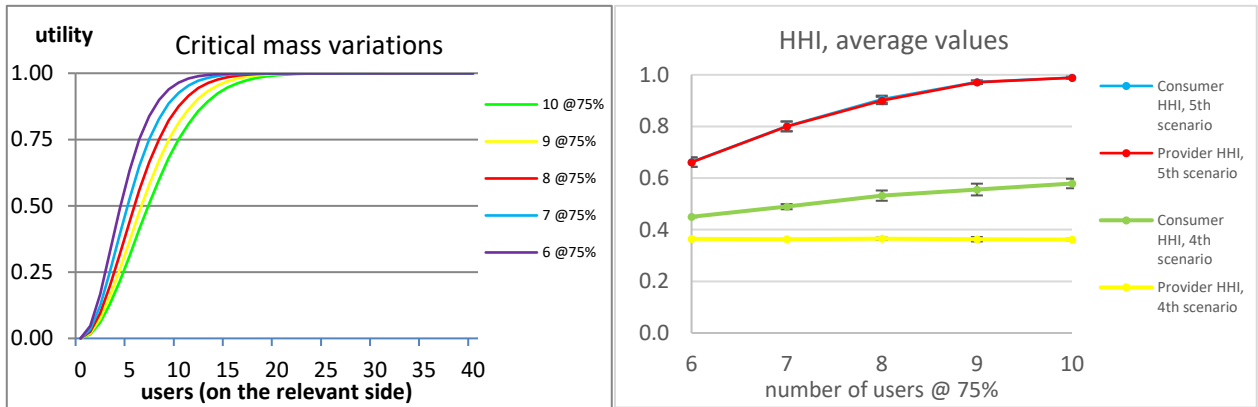


Figure 11: Simulation results for different degrees of network effect: (left) different critical mass cases, (right) HHI index for scenarios 4th and 5th.

In Figure 12 five scenarios are tested for a case in which interoperability allows multihoming. With this purpose, all scenarios are run with a reutilization rate of 0.7, meaning that 0.7 of the investment can be reutilized and therefore 70% of the service providers will multihome and 40% will multihome in all three platforms. A multihoming case is compared with a no-multihoming case, both with high critical mass. The results indicate that service provider multihoming helps to avoid high market concentration on both sides of a platform when switching costs are low. Comparing Figure 12 with a similar analysis on the network effect (Figure 11), the results suggest that multihoming can neutralize the high market concentration due to network effect and its influence is comparable with decreasing the critical mass of users.

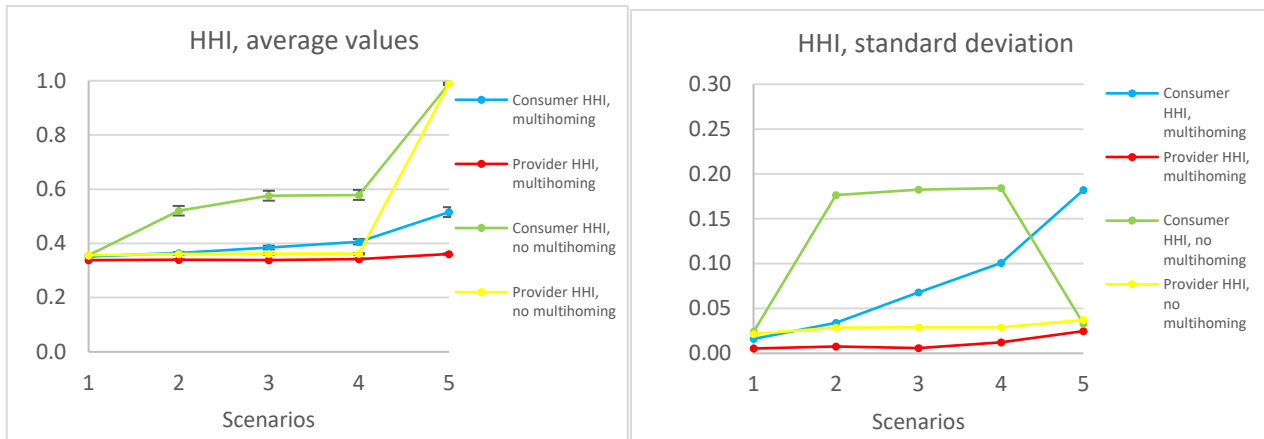


Figure 12: Simulation results for multihoming versus no multihoming cases

Figure 13 (left) performs a sensitivity analysis on multihoming for scenarios 4 and 5, with different reutilization rates, and high critical mass. This figure shows that the positive effect of multihoming in decreasing market concentration is more pronounced from a reutilization rate of 70%. Before this point, the effect is much lower. In practice, this means that most service providers should multihome to avoid high market concentration. In other words, there is a minimum level of interoperability, which promotes market competition. Figure 13 (right) depicts a case where unlike in other scenarios, initial market concentration is high. The five scenarios are run for multihoming (reutilization rate of 70%) and no multihoming. The results for scenario 1 with multihoming (HHI of 0.75) represent an approximation of the initial market concentration. The results for scenarios 3, 4 and 5 shows that lowering switching costs results in lower market concentration when multihoming is allowed. Without multihoming, lowering switching costs when market concentration is high will result in even higher market concentration.

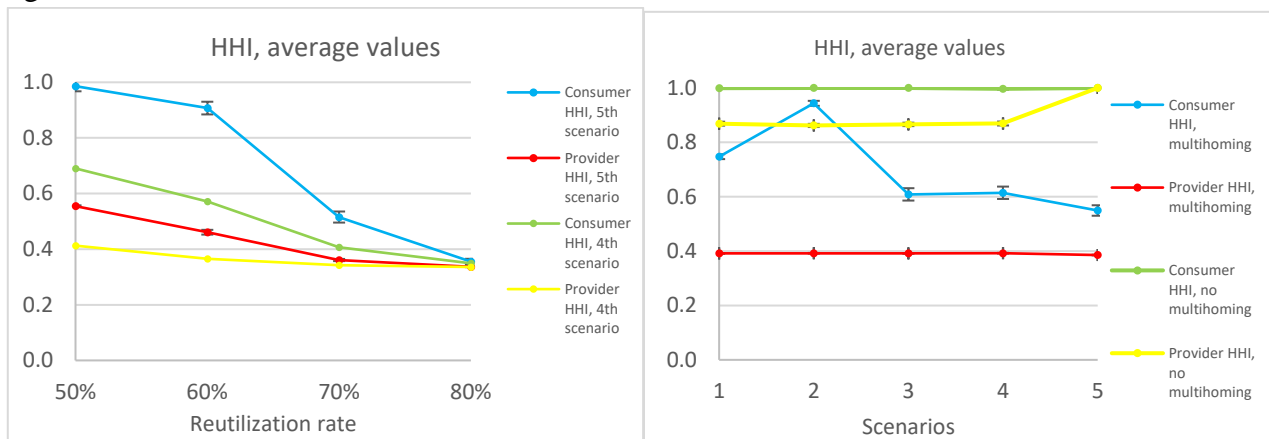


Figure 13: Sensitivity analysis of multihoming

Finally, the five scenarios are run with higher differentiation costs (Figure 14 and Figure 15) and for an adoption case (Figure 16), as introduced earlier in Figure 7. Both cases are run with high critical mass. For the differentiation case, the results show that higher differentiation lightly decreases market concentration with high critical mass. In Figure 15, the distance costs related to differentiation is further varied from low differentiation base case (distance costs equal 1) to a very high differentiation case (distance costs equal 3). These results are intuitive since higher differentiation allows platforms to maintain local monopolies. Figure 16 shows that an adoption process slightly

diminishes market concentration. A reason for this may be that such process adds further dynamisms to the market, since new consumers and service providers entering the market are not locked-in and have more willingness to join the platform which better fits to own needs. However, this figure shows that an adoption process is not significantly varying the results, especially considering the scenario 5.

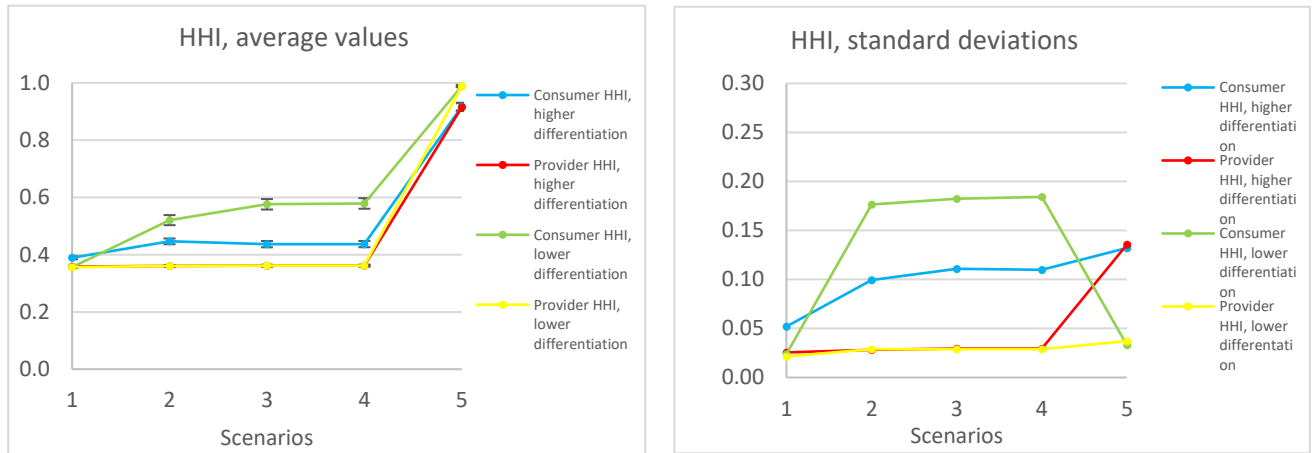


Figure 14: Simulation results for high versus low differentiation

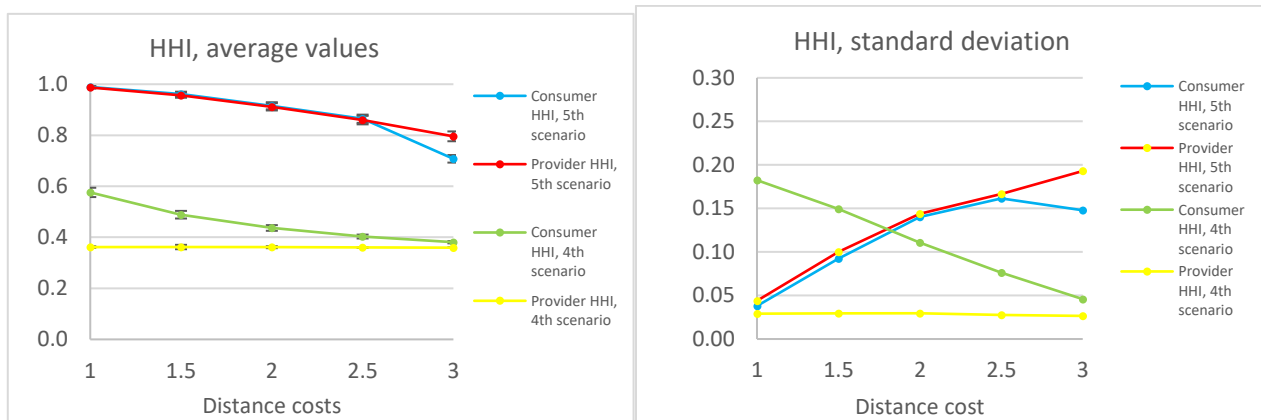


Figure 15: Sensitivity analysis for distance costs (differentiation)

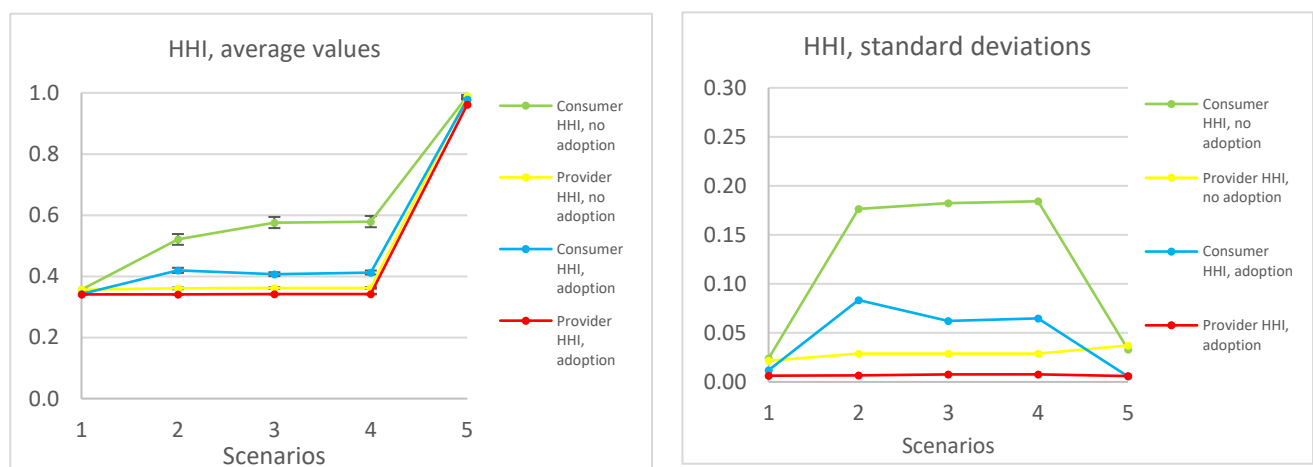


Figure 16: Simulation results for an adoption case

The following

Table 3 summaries the simulation results.

Table 3: Summary of simulation results

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
	High switching costs	Device unbundling	Consumer data portability	Scenarios 2 and 3 combines	Full data portability
Network effect	High critical mass increases market concentration when switching costs are low, especially for scenario 5 (Figure 10)			The strength of critical mass is proportional to an increase in market concentration (Figure 11)	
Multihoming	Multihoming has a strong impact in decreasing market concentration for all scenarios, including scenario 5. When starting from a high market concentration, multihoming even decreases market concentration with low switching costs. (Figure 12, Figure 13)				
				There is an inflection point from which multihoming causes high impact (approx. 70% reutilization in Figure 13)	
Differentiation	Higher differentiation (and unit costs of distance) decreases market concentration by providing to each platform local market power. Its impact is comparatively lower than other market forces (Figure 14)				
				Differentiation costs are proportional to a decrease in market concentration (Figure 15)	
Adoption	An adoption process decreases market concentration for some scenarios (2, 3 and 4) by increasing the dynamics of platform competition (Figure 16)				

Discussion and Conclusions

Internet of things brings new opportunities for established industries and may represent a new source of welfare and efficiency for producers and consumers. However, platform competition creates the risk of monopoly power due to network effects. In this context, cooperation and interoperability provide means to achieve higher social welfare through lower market concentration.

First of all, lowering switching costs may increase market concentration. This is mainly due to network effects. The classic economic theory states that a decrease in switching costs facilitates competition. According to our results, lowering switching costs incentivizes users from different sides to choose the same platform because users on each side value the number of users on the other side and this effect is further stimulated with a stronger network effect. These results are in line with the latest literature in this domain (Chen, 2016; Lam, 2017), even though this is still a recent finding in the economic literature.

The main finding of this work is that provider multihoming can potentially decrease market concentration and thus soften the unwanted effect of decreased switching costs in a scenario with high network effects. This is an important observation since currently regulatory authorities are actively enforcing consumer data sharing, which diminishes switching costs. Moreover, wider interoperability is typically a hard challenge in emerging IoT platforms. This work emphasizes that along with decreasing switching costs, service provider multihoming plays an important role for

assuring a competitive market. In this line, exclusive dealing and similar practices may negatively affect market competition.

While enforcing consumer data sharing may be easier from a regulatory perspective than achieving higher level of interoperability between platforms, this work emphasizes that facilitating data sharing is not enough for assuring a competitive outcome in IoT platforms. In fact, a wider interoperability is needed for incentivizing service provider multihoming. In short, both competition based on decreasing switching costs and cooperation based on platform interoperability are needed for a competitive outcome. In emerging IoT platforms, competitive mechanisms, such as consumer data portability which diminishes consumer switching costs requires cooperative mechanisms, such as provider multihoming which increase the cooperation between platforms. Their effects are not substituting to each other, but they are complementary.

Although mobile health and other emerging IoT platforms such as connected cars can be viewed as advanced IoT domains, they are still in the initial stages of a lifecycle, with low level of industry collaboration and high fragmentation. However, the need for common data formats and communication standards has been realized, and the first attempts of sharing the data between the companies have been made at least in the mHealth domain, as explained earlier. Although data sharing gives more freedom to consumers in choosing a platform provider, according to this study, it may result in *winner-takes-all* situation. After acquiring a high market power, the monopoly platform provider may stop sharing the data with other platforms and lock-in the users to protect own position from potential innovative entrants. On the other hand, a monopoly platform may also have positive implications, since gathering large amounts of data on a single platform may enable more efficient development of machine learning algorithms-based services and applications that would use the data from e.g. wearables. At the same time, industry collaboration required for the implementation of seamless data sharing will have to introduce standardized data models, which will inevitably reduce the cost of service provider multihoming (expressed as a reutilization rate in the model), which, as shown, will decrease the market concentration. Therefore, more attention should be paid to the standardization of data models and devices in mHealth and other verticals.

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